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Long-term association between European and Indian markets on carbon credit price

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ABSTRACT

This study tries to explore cointegration and Granger causality of daily CER prices in European Energy Exchange and Multi Commodity Exchange (MCX) in India in a multivariate framework after controlling euro–rupee exchange rate and Inter-Bank Offer Rate, a measure of country specific risk. Both ARDL bounds tests and Johansen–Juselius maximum likelihood procedures fail to establish a cointegrating relationship among the variables indicating that an arbitrage opportunity exists between these two markets. The study, however, establishes a short-term Granger causality running from change in CER price in European Energy Exchange and exchange rate to Indian exchange. Generalised error variance decomposition of variables indicates that the price of CER at the Indian stock exchange is most endogenous in nature.

Contents

1. Introduction

It has been accepted that increasing concentration of green house gases (GHGs) in the environment is associated with activities that are anthropogenic in nature. In order to address this cause, the United Nations Framework Convention on Climate Change (UNFCCC) laid the foundation of the Kyoto Protocol in 1992. The Kyoto Protocol was eventually adopted on December 11, 1997, under which member countries commit themselves to reduction of four GHGs (carbon dioxide, methane, nitrous oxide and sulphur hexafluoride) along with two groups of gases (which are hydrofluorocarbons and perfluorocarbons). The protocol allows for flexible mechanisms so that the Annex I countries are able to meet their GHGs emissions obligations. These flexible mechanisms include emission trading, clean development mechanism and joint implementation. Emission trading refers to the transfer of permit to discharge a specific volume of pollutant. Under joint implementation projects, any Annex I country can invest in emission reduction projects in any other Annex I country where it is cheaper to reduce emission than at the home country. The credit of

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these reductions in emissions can be applied towards their commitment under the Kyoto Protocol. Clean development mechanism, on the other hand, can benefit the parties which are non-Annex I along with Annex I countries. While non-Annex I countries can achieve sustainable growth through Clean Development Mechanism (CDM), Annex I countries can be benefited in achieving compliance with their emission reduction commitment.

The Clean Development Mechanism (CDM) is one of the key instruments developed under the Kyoto Protocol to facilitate carbon trading. It was the first of the flexible mechanisms to come into effect, with the launch of the regulatory body, the CDM Executive Board in late 2002. It received unexpected support from the developing countries. Key to this support was the CDM's explicitly stated twin objectives of not only emissions reductions for industrialised countries, but also accelerated sustainable development in developing nations. By providing investment incentives, CDM acts as an aid to project finance in host countries, encouraging sustainable development through the adoption of cleaner energy sources, or more efficient industrial processes.

The parties to the convention have been meeting annually from 1995 at the Conferences of the Parties (COP) to assess the progress of UNFCCC. The objective of these COPs is to strengthen the provisions of UNFCCC and contain anthropogenic emissions of GHGs. COP 15 (Copenhagen: 2009) failed to provide a successor to the Kyoto Protocol. This increased uncertainty about the future of the carbon markets. However, COP 16 (Cancun: 2010) was relatively more successful and a new fund was designed for climate finance. The aim of this fund was to channel money, from the developed to developing nations, to protect developing nations from the impacts of climate change and to assist them in low-carbon development. A framework was also established to reduce global deforestation and forest degradation in developing countries. COP 17 (Durban: 2011) was also successful as a Green Climate Fund was established and an agreement was reached to negotiate a more inclusive treaty. Decision was also taken regarding the second commitment period for the Kyoto Protocol. Thus, the steps initiated at Cancun for emission reduction were implemented at Durban.

Certified Emission Reductions (CERs) are carbon credits generated by CDM projects which have completed the registration process. Majority of these projects have been in China and India. These projects generate primary Certified Emission Rights (pCERs) which are substitutable for emissions in the European Union Emission Trading System (EU ETS). Since 2007, CDM credits have been traded in the secondary markets as well (sCERs). Each CER represents the abatement of one tonne of carbon dioxide equivalent. CERs are issued by the CDM Executive Board once estimated abatement volumes have been validated independently, and a stringent verification process is in place for ongoing monitoring. As of March 31, 2012 the total number of CERs issued was 909,900,908 against 951,933,749 CERs requested.[2] This number is expected to grow in future with the implementation of more CDM projects all across the world [1].

Despite the growth and importance of carbon market, relevant academic research beyond the scope of environmental economics and policy has been very limited. The empirical research in this domain has been concentrated entirely on the European Union Emissions Trading Scheme (EU ETS) markets [2–5] as they are the most liquid and most developed markets. Limited studies have been conducted in the area of CER price dynamics.

Mizrach [6] analysed the market structure and common factors of emission reduction instruments in Europe and North America. His study reveals that the spot and near-term futures expiries in case of Eurpoean Union Allowances (EUAs) are cointegrated across exchanges in Europe and North America. There have also been researches focused primarily at European carbon markets. Certain studies have studied the price dynamics of EU ETS and have found long-term cointegrating relationships between various EU ETS instruments [2–5]. Koop and Tole [7] explored the relationship between spot and future prices of EUAs and CER price. They found evidence of contemporaneous causality between their variables of study. Kapoor [8] modelled time-varying volatility of CER prices at European Energy Exchange and found changes in volatility between two successive COPs.

Such studies have taken into consideration the prices at the European and American exchanges which are exclusively buyer economies in case of carbon credit trading. The research has been extremely sparse in the study of CER price dynamics taking into account the developing economies like India and China, which are the major suppliers of CER across the globe. The present study tries to bridge the gap by exploring cointegration and Granger causality between Indian and European CER markets.

CER trading started in India in January 2008 with MCX being the first Asian commodity exchange to launch futures trading in carbon credit contract. Since then, similar products are being traded at Indian and European energy exchanges. As described above, empirical research has established stable long term association among buyer economies of carbon credit contracts [2–7]. However, no significant work has explored the relationship of CER prices between carbon credit markets at buyer and seller economies respectively. Therefore, this study aims to explore the association of CER prices at Indian and European energy markets.

This study uses a multivariate approach, which is always preferred over a bivariate approach because it avoids specification bias due to omission of relevant variables. The study also employed autoregressive distributed lag (ARDL) bounds testing approach of cointegration developed by Pesaran and Shin [9] and Pesaran et al. [10] which has been complemented by Johansen–Juselius maximum likelihood procedure [11] to provide a sensitivity check on the empirical results [9–11].

The remainder of this paper is organised as follows. Section 2 describes the data in detail. Section 3 discusses the econometric methodology. Section 4 presents empirical analysis and discussion of results. Section 5 presents the summary and concludes.

2. Data descriptions

This study considers following four variables

1. The daily price of CER contract is taken from the MCX (Multi Commodity Exchange) which is a leading commodity exchange in India. The price of CER is quoted in INR.
2. CER prices on European Energy Exchange (denoted by EEX). It consists of daily price observations of secondary CERs for futures contracts expiring in December 2012 listed on the European Energy Exchange (EEX). The price of CER futures contracts on EEX are quoted in €.
3. Euro–Rupee exchange rate (denoted by EX). Exchange rate can be an important determinant of the prices on the Indian commodity market. In a study of price dynamics between two exchanges with different currencies, exchange rate might prove to be a significant variable. Source of this rate was the website of the Reserve Bank of India.
4. Mumbai Inter-Bank Offer Rate (denoted by MIBOR). MIBOR is a measure of country specific risk in a case where we study the prices of a commodity at exchanges in two different countries. Previous studies have also found country level risks in similar

[2] Retrieved from UNFCCC website http://cdm.unfccc.int/Statistics/Public/CDMinsights/index.html

scenarios to be significant. Therefore, three months' MIBOR has also been considered as an endogenous variable in the VAR model. Time series data for MIBOR has also been taken from the Reserve Bank of India.

The data spans from 12/19/2009 to 11/24/2011. This period is chosen based on the fact that it begins after Copenhagen Summit concluded and ends just before Durban Summit, covering Cancun Summit which was held in the end of 2010. All the variables are log-transformed.

3. Econometric methodology

The study employs various cointegration techniques to examine long-term equilibrium relationships among the variables. The study also examines Granger causality and generalised error variance decomposition analysis to establish the direction of causations and impact of various shocks in the system.

Cointegration can be defined as a systemic co-movement among two or more macroeconomic variables over the long run. The presence of cointegration among the variables rules out the possibility of "spurious" correlation. In many cases, economic theory tells us that two or more variables should be cointegrated and a test for cointegration is the test of the theory.

In the past two decades, after the seminal work of Engle and Granger [12], cointegration techniques have been extensively used in empirical research to examine the long run relationship of economic variables in a bivariate or multivariate framework. Pesaran et al. [10] introduced Autoregressive-Distributed lag (ARDL) bounds tests approach for cointegration. One of the main benefits of ARDL bounds tests procedure is that it can be employed regardless of whether the underlying variables are stationary i.e. I(0), integrated of order one i.e. I(1) or fractionally integrated. Second, the long-run and short-run parameters of the model in question can be estimated simultaneously. Third, the small sample properties of bounds testing approach are superior to that of multivariate cointegration [13].

3.1. Johansen–Juselius (J–J) maximum likelihood procedure for cointegration

Engle and Granger [12] showed that if the two series X and Y (say) are individually I(1) and share a common stochastic trend then there exists a long-run relationship among the variables or, in other words, variables are cointegrated. The presence of cointegration among the variables rules out the possibility of "spurious" correlation. Furthermore Granger's Representation Theorem demonstrates how to model a cointegrated I(1) series in a vector autoregression (VAR) format. VAR can be constructed either in terms of the level of the data or in terms of their first differences, i.e. I(0) variables, with the addition of an error correction term (ECT).

Let us consider an unrestricted VAR of order p represented by

$$y_t = a_0 + a_1 t + \sum_{i=1}^{p} \Phi_i y_{t-i} + \Psi w_t + u_t \tag{1}$$

where y_t is a $(n \times 1)$ vector of endogenous I(1) variables, t is the linear time trend, a_0 and a_1 are $(n \times 1)$ vectors, w_t is a $(q \times 1)$ vector of exogenous variables and u_t is a $(n \times 1)$ vector of unobserved disturbances where $u_t \sim N\,(0, \Omega)$, $t = 1, 2, \ldots, T$.

Let $\Delta y_t = y_t - y_{t\ -1}$, then a convenient reparameterization of Eq. (1) can be written as

$$\Delta y_t = a_0 + a_1 t + \sum_{i=1}^{p-1} \Pi_i^* \Delta y_{t-i} - \Pi^* y_{t-1} + \Psi w_t + u_t \tag{2}$$

where both Π_i^* and Π^* are of dimension $(n \times n)$. Π^* is the long-run multiplier matrix whereas Π_i^* capturing the short-run dynamic effects. This is VAR approach of Johansen [15,16] and Johansen and Juselius [11] to investigate the cointegration properties of a system. They provide a full maximum likelihood procedure for estimation and testing within the VAR framework. Since u_t is stationary, the rank, r, of the matrix Π^* determines how many linear combinations of y_t are stationary. If $r = n$, all y_t are stationary and if $r = 0$ so that $\Pi^* = 0$, Δy_t is stationary and all linear combination of $y_t \sim$I(1). For $0 < r < n$ i.e., when Π^* is rank deficient, there exists r cointegrating vectors or, in other words, r linear stationary combination of y_t. In this case Π^* can be factored as $\alpha\beta^{\prime}$ where both α and β are $(n \times r)$ matrices. The cointegrating vectors of β are the error correction mechanism in the system while α contains the adjustment parameters.

The cointegrating rank, r, can be formally tested with two statistics. The first is the maximum eigenvalue test. Denoting the estimated eigenvalues as λ_i^*, $i = 1, 2, \ldots, n$, the maximum eigenvalue test is given by

$$\lambda_{max} = -T \log(1 - \lambda_{r+1}^*) \tag{3}$$

where the appropriate null hypothesis is $r = \text{g}$ cointegrating vectors against the alternative hypothesis that $r \leq g + 1$.

The second is the trace statistic and is computed as

$$Trace = -\sum_{i=r+1}^{n} T \log(1 - \lambda_i^*) \tag{4}$$

where the null hypothesis is $r = \text{g}$ against the alternative hypothesis $r \leq g$

3.2. ARDL bounds tests approach for cointegration.

An ARDL model is a general dynamic specification, which uses the lags of the dependent variable and the lagged and contemporaneous values of the independent variables, through which the short-run effects can be directly estimated, and the long-run equilibrium relationship can be indirectly estimated. ARDL technique involves estimating the following unrestricted error correction model:

$$\begin{aligned} DMCX_t = a_{0MCX} &+ \sum_{i=1}^{n} b_{iLoil} DMCX_{t-i} + \sum_{i=1}^{n} c_{iMCX} DEEX_{t-i} \\ &+ \sum_{i=1}^{n} d_{iMCX} DEX_{t-i} + \sum_{i=1}^{n} e_{iMCX} DMIBOR_{t-i} \\ &+ \sigma_{1MCX} MCX_{t-1} + \sigma_{2MCX} EEX_{t-1} \\ &+ \sigma_{3MCX} MIBOR_{t-1} + \sigma_{4MCX} EX_{t-1} + \varepsilon_{1t} \end{aligned} \tag{5}$$

$$\begin{aligned} DEEX_t = a_{0EEX} &+ \sum_{i=1}^{n} b_{iEEX} DEEX_{t-i} + \sum_{i=1}^{n} c_{iEEX} DMCX_{t-i} \\ &+ \sum_{i=1}^{n} d_{iEEX} DEX_{t-i} + + \sum_{i=1}^{n} e_{iEEX} DMIBOR_{t-i} \\ &+ \phi_{1EEX} EEX_{t-1} + \phi_{2EEX} MCX_{t-1} \\ &+ \phi_{3EEX} EX_{t-1} + \phi_{4EEX} MIBOR_{t-1} + \varepsilon_{2t} \end{aligned} \tag{6}$$

$$\begin{aligned} DEX_t = a_{0EX} &+ \sum_{i=1}^{n} b_{iEX} DEX_{t-i} + \sum_{i=1}^{n} c_{iEX} DMCX_{t-i} \\ &+ \sum_{i=1}^{n} d_{iEX} DEEX_{t-i} + \sum_{i=1}^{n} e_{iEX} DMIBOR_{t-i} \\ &+ \theta_{1EX} EX_{t-1} + \theta_{2EX} MCX_{t-1} \\ &+ \theta_{3EX} EEX_{t-1} + \theta_{4EX} MIBOR_{t-1} + \varepsilon_{3t} \end{aligned} \tag{7}$$

$$\begin{aligned} DMIBOR_t = a_{0MIBOR} &+ \sum_{i=1}^{n} b_{iMIBOR} DEX_{t-i} + \sum_{i=1}^{n} c_{iMIBOR} DMCX_{t-i} \\ &+ \sum_{i=1}^{n} d_{iMIBOOR} DEEX_{t-i} + \sum_{i=1}^{n} e_{iMIBOR} DMIBOR_{t-i} \end{aligned}$$

$$+\tau_{1MIBOR}EX_{t-1}+\tau_{2MIBOR}MCX_{t-1}+\tau_{3MIBOR}EEX_{t-1}+\tau_{4MIBOR}MIBOR_{t-1}+\varepsilon_{4t} \quad (8)$$

here 'D' is the first difference operator. The null hypothesis of no cointegration among the variables in Eq. (1) is

H_0: $\sigma_{1MCX}=\sigma_{2MCX}=\sigma_{3MCX}=\sigma_{4MCX}=0$, which is denoted as $\mathbf{F_{MCX}}$(*MCX|EEX, EX, MIBOR*). Similarly for Eq. (2), H_0: $\varphi_{1EEX}=\varphi_{2EEX}=\varphi_{3EEX}=\varphi_{4EEX}=0$, which is denoted as $\mathbf{F_{EEX}}$(*EEX|EX, MCX, MIBOR*) and so on.

F-test is used to examine whether a cointegrating relationship exists among the variables. The *F*-test has a non-standard distribution which depends upon whether variables included in the ARDL model are (a) I(0) or I(1); (b) the number of regressors; (c) whether the ARDL model contains an intercept and/or a trend; and (d) the sample size. Two sets of critical *F* values have been provided by Pesaran and Shin [9] and Pesaran et al. [10] for large samples and by Narayan [13] for sample size ranging from 30 to 80, where one set assuming that all variables in ARDL model are I(1) and another assuming that all variables are I(0) in nature. It is important to note that the critical values based on large sample size deviates significantly from that of small sample size.

If computed *F*-statistics falls outside the band, a conclusive decision can be taken without needing to know whether the underline variables are I(0) or I(1). Cointegration exists only if the computed *F*-statistics is higher than the upper bound critical value while inference remains inconclusive if the computed *F*-statistics falls within the critical band.

3.3. Granger causality

Granger causality is a statistical test to ascertain whether one series is useful in predicting the other. Engle and Granger [12] showed that if the series *X* and *Y* (for example) are individually I(1) and cointegrated then there would be a causal relationship at least in one direction between those two series. However, the direction of causality can be detected through the Vector Error Correction model (VECM) of long-run cointegrating vectors.

In our case, tests for Granger causality can be done through following equations

$$DMCX_t=\beta_{10}+\sum_{i=1}^{p}\beta_{11i}DMCX_{t-i}+\sum_{i=1}^{p}\beta_{12i}DEEX_{t-i}+\sum_{i=1}^{p}\beta_{13i}DEX_{t-i}+\sum_{i=1}^{p}\beta_{14i}DMIBOR_{t-i}+\beta_{15}\varepsilon_{t-1}+u_{1t} \quad (8.1)$$

$$DEEX_t=\beta_{20}+\sum_{i=1}^{p}\beta_{21i}DEEX_{t-i}+\sum_{i=1}^{p}\beta_{22i}DMCX_{t-i}+\sum_{i=1}^{i}\beta_{23i}DEX_{t-i}+\sum_{i=1}^{p}\beta_{24i}DMIBOR_{t-i}+\beta_{25}\varepsilon_{t-1}+u_{21t} \quad (8.2)$$

$$DEX_t=\beta_{30}+\sum_{i=1}^{p}\beta_{31i}DEX_{t-i}+\sum_{i=1}^{p}\beta_{32i}DEEX_{t-i}+\sum_{i=1}^{p}\beta_{33i}DMCX_{t-i}+\sum_{i=1}^{p}\beta_{34i}DMIBOR_{t-i}+\beta_{35}\varepsilon_{t-1}+u_{3t} \quad (8.3)$$

$$DMIBOR_t=\beta_{40}+\sum_{i=1}^{p}\beta_{41i}DMIBOR_{t-i}+\sum_{i=1}^{p}\beta_{42i}DEEX_{t-i}+\sum_{i=1}^{p}\beta_{43i}DMCX_{t-i}+\sum_{i=1}^{p}\beta_{44i}DEX_{t-i}+\beta_{45}\varepsilon_{t-1}+u_{4t} \quad (8.4)$$

where βs are parameters to be estimated, u_ts are the serially uncorrelated error terms, and ε_{t-1} is the error correction term (ECT). The *F*-statistics on the lagged explanatory variables of the ECT indicates the significance of the short-run causal effects. The *t*-statistics on the coefficients of the lagged error-correction term indicates the significance of the long-run causal effect.

If the series are I(1) but not cointegrated, causality test may give misleading results unless the data are transformed to induce stationarity.

3.4. Generalised forecast error variance decomposition (GFEVD)

The decomposition of variance measures the percentage of a variable's forecast error variance that occurs as the result of a shock from a variable in the system. Therefore, by employing this technique, one can find the relative importance of a set of variables that affect variance of another variable.

GFEVD can be defined as

$$\frac{\sigma_{ij}^{-1}\left[\sum_{l=0}^{n}\left(e^{/}G_l\Sigma e_j\right)^2\right]}{\sum_{l=0}^{n}\left(e_i^{/}G_l\Sigma G_{ll}^{i}\Sigma e_i\right)^2} \quad (9)$$

where $G_n=\Phi_1G_{n-1}+\Phi_2G_{n-2}+\cdots+\Phi_pG_{n-p}$; $n=1, 2, 3\ldots$ $G_o=I$, $G_n=0$ for $n<0$ and e_j is a (3×1) selection vector with unity as its *j*th element and zero elsewhere and covariance $\sum=\sigma_{ij}$.

It is important to note that unlike the standard orthogonalized approach, the generalised approach of Pesaran and Shin [14] is not sensitive to the ordering of variables in the VAR system. Unlike orthogonal approach, the values for generalised variance decomposition at each horizon do not necessarily sum to one.

Table 1
Unit root test results.

VARIABLES	Level (with intercept and trend)		Ist Difference (with intercept but no trend)	
	ADF	PP	ADF	PP
MCX	−0.80	−0.82	−22.60	−22.60
	(0.96)	(0.96)	(0.00)	(0.00)
EEX	1.09	0.59	−20.82	−21.10
	(0.99)	(0.99)	(0.00)	(0.00)
EX	−2.12	−2.44	−23.72	−44.36
	(0.53)	(0.36)	(0.00)	(0.00)
MIBOR	−0.43	−1.04	−30.03	−29.07
	(0.99)	(0.94)	(0.00)	(0.00)

figures in brackets are probability values.

Table 2
Bounds testing for cointegration.

F-statistics	**Without a time trend**		**With a time trend**	
$\mathbf{F_{MCX}}$ (*MCX|EEX, EX, MIBOR*)	3.2517		3.8685	
$\mathbf{F_{EEX}}$ (*EEX|EX, MCX, MIBOR*)	1.5596		2.2615	
$\mathbf{F_{EX}}$(*EX|MCX, EEX, MIBOR*)	2.4615		1.1688	
$\mathbf{F_{MIBOR}}$ (*MIBOR|MCX, EEX, EX*)	2.1151		1.8081	
***F-critical at 5% level**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
	3.219	4.378	4.066	5.119

4. Empirical analysis and discussion of results

A three-stage Modelling procedure has been employed in this study. The first step tests for the order of integration of the natural logarithm of the variables using Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) statistics.

The second stage involves investigating cointegration relationship among the variables by employing ARDL bounds testing approach [9,10], complemented by Johansen–Juselius maximum likelihood procedure [11,15,16].

The third stage (or second if cointegration is rejected) involves constructing standard Granger–type causality tests, augmented where appropriate with a lagged error correction term followed by GFEVD due to shocks in the system.

In the first stage the order of integration of the variables is investigated. This is important because we need to be sure of the order of integration of the time series before any econometric test is performed. Table 1 presents the results of unit root tests on the natural logarithms of the levels and the first differences of the variables other than MIBOR since the variable is already in percentage terms. On the basis of Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests, the null hypothesis of a unit root cannot be rejected. This suggests that the series are not stationary or I(0). Stationarity is obtained by running the similar test on the first difference of the variables, indicating all the series are I(1) in nature.

Next the bounds testing procedure has been employed to detect cointegration relationship in Eqs. (1)–(4). The optimal order of lags for cointegration tests are selected based on Schwarz–Bayessian (SBC) information criteria as suggested by Pesaran et al. [10].

The results of the bounds test for cointegration are reported in Table 2. The bounds test indicates that cointegration is not present among these variables. This is because when *MCX*, *EEX*, *EX* and *MIBOR* are dependent variables, $\mathbf{F_{MCX}}$(*MCX*|*EEX*, *EX*, *MIBOR*), $\mathbf{F_{EEX}}$(*EEX*|*EX*, *MCX*, *MIBOR*), $\mathbf{F_{EX}}$(*EX*|*MCX*, *EEX*, *MIBOR*) and $\mathbf{F_{MIBOR}}$(*MIBOR*|*MCX*, *EEX*, *EX*) are lower than the upper bound critical value at the 5% level of significance. This is true for both with and without a time trend.

In addition to the bounds test of cointegration, Johansen maximum likelihood procedure is employed to check the robustness of the ARDL bounds test results. Referring to Table 3, both maximal eigenvalue test and trace test reveal that the null hypothesis of no cointegration, i.e. $r=0$ among the variables cannot be rejected at 5% level of significance. In such a case where both the above-mentioned tests for cointegration reveal no cointegration, it can be concluded that there is absence of long term stable relationship between the CER prices in European and Indian markets. This also means that there exists information asymmetry between the two markets.

In the next stage, we have taken first difference of all the series in order to make them stationary and tried to model it through an unrestricted vector auto-regression (VAR) framework to explore short-run dynamics among the variables.

Table 3
Johansen–Juselius likelihood cointegration tests.

H_o	λ_{trace}	5% CV	λ_{max}	5% CV
$r=0$	44.53	63.882	16.81	32.12
$r\leq 1$	27.72	42.92	13.72	25.82
$r\leq 2$	14.00	25.87	9.22	19.39
$r\leq 3$	4.78	12.52	4.78	12.52

An unrestricted VAR of order p can be represented by

$$y_t = a_0 + \sum_{i=1}^{p} \Phi_i y_{t-i} + u_t \quad (10)$$

where y_t is a $(n\times 1)$ vector of endogenous variables, a_0 is $(n\times 1)$ vectors, and u_t is a $(n\times 1)$ vector of unobserved disturbances where $u_t \sim N\ (0,\ \Omega)$, $t=1,\ 2,\ldots,\ T$.

Table 4
Granger causality test results.

Dependent variable	*DMCX*	*DEX*	*DEEX*	*DMIBOR*
For the entire period (12/18/09–11/24/11)				
DMCX	–	59.51 (0.00)	1780.87 (0.00)	0.58 (0.90)
DEX	5.81 (0.11)	–	3.75 (0.29)	0.26 (0.97)
DEEX	2.0 (0.57)	5.37 (0.15)	–	5.79 (0.12)
DMIBOR	9.20 (0.03)	6.21 (0.09)	6.48 (0.09)	–
For sub-period I (12/18/09–11/28/10)				
DMCX	–	11.96 (0.00)	584.73 (0.00)	2.78 (0.43)
DEX	3.47 (0.32)	–	0.82 (0.85)	0.42 (0.94)
DEEX	0.69 (0.88)	6.79 (0.08)	–	3.53 (0.32)
DMIBOR	9.16 (0.03)	6.65 (0.08)	2.87 (0.41)	–
For sub-period II (12/11/10–11/24/11)				
DMCX	–	298.39 (0.00)	2204.41 (0.00)	1.07 (0.78)
DEX	1.29 (0.73)	–	0.07 (0.99)	0.50 (0.91)
DEEX	1.09 (0.78)	4.48 (0.21)	–	2.91 (0.41)
DMIBOR	4.63 (0.20)	8.23 (0.04)	6.27 (0.10)	–

Figures in brackets are probability values.

Table 5
Generalised variance decomposition results.

Horizon	*DMCX*	*DEEX*	*DEX*	*DMIBOR*
Variance decomposition of DMCX				
1	0.25534	0.7207	0.028573	0.001111
5	0.24356	0.699	0.04018	0.019215
10	0.24335	0.69821	0.041314	0.019225
20	0.24335	0.69821	0.041317	0.019226
Variance decomposition of DEEX				
1	0.025164	0.99399	0.002608	0.004582
5	0.026605	0.9778	0.010937	0.010168
10	0.026601	0.97762	0.011093	0.01017
20	0.026601	0.97762	0.011094	0.01017
Variance decomposition of DEX				
1	0.019341	0.001595	0.99294	0.002448
5	0.023371	0.003698	0.98542	0.003108
10	0.02339	0.003707	0.98536	0.003119
20	0.02339	0.003707	0.98536	0.003119
Variance decomposition of DMIBOR				
1	0.01381	7.00E-05	0.002855	0.99042
5	0.017921	0.001813	0.014664	0.97573
10	0.017988	0.001865	0.014718	0.97558
20	0.017988	0.001865	0.01472	0.97557

In the present case,

$$y_t = \begin{bmatrix} DMCX \\ DEEX \\ DEX \\ DMIBOR \end{bmatrix}$$

Optimum lag length of the VAR, according to AIC criteria, appears to be three. The absence of residual serial correlation of the individual equations has also confirmed the correct order of VAR selection.

Next, Granger causality tests were performed to investigate the causal relationships of the variables. Intuitively, prices of CER in the Indian commodity market should be affected by price fluctuation in the European Energy market. With increasing integration of economies of the world, prices of asset should move together in all markets of the world. There might, however, be a possibility that the relationship of these variables would have changed pre and post Cancun Summit as certain crucial decisions on carbon trading were finalised then. Therefore, the entire period has further been divided into two sub-periods; pre and post of Cancun Agreements and Granger causality among the variables have been examined for the two sub-periods along with entire data span.

Results of the Granger causality test are summarised in Table 4. Since the series are not cointegrated, so there will be no error correction term (ECT). The null hypothesis of non-causality from DEEX and DEX to DMCX cannot be rejected at 5% level of significance indicating unidirectional Granger causality running from change in CER price at EEX and Euro–Rupee exchange rate to change in CER price at MCX. This causality remains unchanged for both the sub-periods under consideration as well. The study also indicates Granger causality running from DMCX to DMIBOR without any feedback effect for the entire period as well as for phase I and from DEX to DMIBOR in phase II. This indicates that volatility in CER price at EEX would induce a short-term fluctuation in CER price at MCX in India. In the same way, volatility in the Euro–Rupee exchange rate would exhibit a similar effect in CER price at MCX in India.

Detecting Granger causality is essentially an in-sample phenomenon, which is useful in discriminating Granger exogeneity or endogeneity of the dependent variable in the sample period, but is unable to deduce the degree of exogeneity of the variables out of sample period. To address this, in the next stage, we employed generalised forecast error variance decomposition analysis. Variance decomposition separates the variation in an endogenous variable into the component shocks to the model, and provides information about the relative importance of each random innovation in affecting the variables in the VAR model. The decomposed variances allow researchers to assess the relative importance of an individual variable due to its own shocks and the shocks of other variables. The results are presented in Table 5 over a horizon of 20 days. From the results it is clear that most of forecast error variance (FEV) of the variables can be explained by their own shocks other than DMCX. The initial impact of DEEX on FEV of DMCX is around 72 per cent and around 70 per cent in 1st and 20th day, which are higher than any other variables in the system. DEX and DMIBOR explain about 2.2–4 per cent and 0.1–1.9 per cent respectively of the FEV of DMCX in entire horizon. DMCX explains 25–24 per cent of its own FEV. Results indicate that the price of CER at the Indian stock exchange is most endogenous in nature.

5. Summary and conclusion

The study explores cointegration and Granger causality between CER prices at European and Indian exchanges in a multivariate framework by incorporating euro–rupee exchange rate and inter-bank offer rate. Contrary to other studies [2,4,6] this study fails to establish a long-run equilibrium relationship among the variables. The absence of cointegration would mean that there is information asymmetry between the two CER markets. An arbitrage opportunity thus, exists between these two markets.

The study, however, establishes a short-term Granger causality from change in carbon credit prices in European Energy Exchange to Indian exchange. Short-term causality from change in exchange rate to change in CER prices at Indian exchange is also established.

The reason for this causality can be attributed to the difference in information efficiency at the two exchanges. European Energy Exchange is a well established CER exchange and therefore would exhibit information efficiency. All publicly available information would be incorporated in the price of CER at the EEX. However, there is a lag before this information is exhibited in the prices at the Indian commodity exchange (MCX) reflecting information inefficiency. Similarly, foreign exchange market is also informational efficient and any new information affecting the economy is immediately reflected in the currency's exchange rate fluctuation. It is also indicated that country-specific risks as denoted by MIBOR also play an important role for CER price discovery in India.

Thus, there remains a need for information dissemination among the market participants of CER at MCX. Although India is one of the major suppliers of CER, traders at the Indian exchange do not have the information of the same quality as their peers in the developed economies. Had there been adequate quality information available for the traders at the Indian exchange, the prices of CER would have been be integrated with the rest of the world.

Currently, the carbon markets in Europe are in a state of acute crisis. CERs are being traded below 1 euro per ton in 2013 after a high of over 13 euro per ton in 2009. Numerous reasons can be associated with such a fall. Firstly, the debt crisis in Euro-zone has made the investments in CDM unproductive. Also, the EU ETS (Emission Trading System) has been facing uncertainty because of oversupply of CERs while the demand has been stagnant as the COP 18 at Doha did not generate any further motivation to reduce emissions. The policy makers in Europe have to address the issue of whether to cut back the oversupply or to push economic reforms in order to stabilise the fallen prices. However, a report by Thomson Reuters titled "Carbon 2013 – At a tipping point" expects CER prices to improve in future with the improvement of economic crisis in Europe [1].

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